EVALUATING IMPORTANCE RATINGS AS AN ALTERNATIVE TO MENTAL MODELS IN PREDICTING DRIVING CRASHES AND MOVING VIOLATIONS

A Thesis

by

JENNIFER NICOLE MCDONALD

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2011

Major Subject: Psychology

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Approved by:

Chair of Committee,	Winfred Arthur, Jr.
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ABSTRACT

Evaluating Importance Ratings as an Alternative to Mental Models
in Predicting Driving Crashes and Moving Violations. (May 2011)
Jennifer Nicole McDonald, B.S., North Dakota State University
Chair of Advisory Committee: Dr. Winfred Arthur, Jr.

The present study investigated the extent to which importance ratings (i.e., a measure of perceived importance for driving-related concepts) are a viable alternative to traditional mental model assessment methods in predicting driving performance. Although mental models may predict driving–related outcomes—crash involvement and moving violations—common mental model assessment techniques are associated with administrative limitations and challenges, which can affect how valid mental models are as assessments of knowledge structure. Importance ratings, as a measure of driving-related knowledge that may be associated with fewer administrative limitations, were hypothesized to provide equal predictive validity for driving–related performance outcomes in a sample of undergraduate students.

To investigate the extent to which the measurement of mental models and importance ratings contribute to the prediction of driving crashes and moving violations, students completed Pathfinder, a common computer-based mental model assessment method, and paper-and-pencil importance ratings. In addition, students completed a test of driving knowledge and reported driving behaviors and outcomes including at-fault

crashes and moving violations that occurred over the past five years (i.e., from 2005 to 2009).

A group of expert drivers completed mental model and importance ratings assessments as well. Data across expert raters were combined and analyzed for appropriateness to serve as referent scores for each assessment. Students' mental model accuracy as well as importance rating accuracy was based on the extent to which student mental models and ratings agreed with those provided by the group of expert drivers.

The results suggest that importance rating and mental model accuracy predicted crash involvement and moving violations. Whereas mental model accuracy was a stronger predictor of the number of moving violations, importance rating accuracy predicted the number of at-fault crashes slightly better than mental models. Although inconclusive, these results suggest that importance ratings may be a viable alternative to traditional mental model assessment in predicting some driving outcomes. Future research is warranted on importance ratings and other alternative mental model assessments.

DEDICATION

To my parents, for their endless support and encouragement.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Arthur, and my committee members, Dr. Payne and Dr. Martin, for their guidance and assistance with the development of this thesis.

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Special thanks to my husband, Jeremy, for his incredible support and patience.

TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION AND LITERATURE REVIEW

Knowledge organization has been of interest to industrial and organizational (I/O) psychologists as evidenced by numerous journal articles (e.g., Day, Arthur, & Gettman, 2001; Edwards, Day, Arthur, & Bell, 2006; Mohammed & Dumville, 2001; Schuelke et al., 2009). Researchers argue that knowledge involves not only knowledge of facts and concepts, but also a structural component that reflects how information is organized (Kraiger, Ford, & Salas, 1993). Specifically, researchers propose that knowledge is multifaceted, and can be conceptualized as consisting of declarative knowledge, procedural knowledge, knowledge organization, and cognitive strategies and skills (e.g., meta-cognition) (Kraiger et al., 1993). Early in skill acquisition, trainees focus on declarative knowledge, but as training (or experience) progresses, they focus more on procedural knowledge. As procedural knowledge increases, trainees start to develop meaningful structures for organizing knowledge. This has led several researchers to focus on the organization of knowledge rather than the amount or type of knowledge (e.g., Kraiger et al., 1993; Rouse & Morris, 1986). However, assessments of knowledge organization are associated with long administration times and limitations regarding the extent to which concepts can be sampled from complex task domains. As such, the primary objective of the present study is to investigate the extent to which importance ratings can serve as substitutes for mental models (a common operationalization of knowledge organization) in predicting driving outcomes.

This thesis follows the style of *Journal of Applied Psychology.*

Mental Models

Mental models are structures that contain organized knowledge in meaningful patterns, which are stored in memory (Johnson–Laird, 1983; Rouse & Morris, 1986). Mental models contain information regarding concepts, features, and the relationships between them (Rips, Shoben, & Smith, 1973). Similar concepts and terms include associative nets, cognitive structures, conceptual frameworks, mental maps, knowledge structures, and schemas (Dorsey, Campbell, Foster, & Miles, 1999; Johnson–Laird, 1983; Kraiger et al., 1993; Rouse & Morris, 1986). Although there may be subtle differences between these terms, the term mental model will be used for the purpose of the present work.

Concomitant with the varying terminology for mental models (Rouse & Morris, 1986), a variety of techniques have been used to operationalize mental models, including network scaling, multidimensional scaling, interactively elicited cause mapping, and text–based cause mapping (Cooke, Salas, Cannon–Bowers, & Stout, 2000; Mohammed, Klimoski, & Rentsch, 2000). However, network scaling—using Pathfinder—is possibly the most widely used technique in academic journals (Schuelke et al., 2009). Pathfinder provides a number of indices that characterize mental models, such as accuracy and coherence. Accuracy represents the degree to which a specified mental model adequately represents a given knowledge or skill domain. Coherence is a metric of internal consistency and reflects a knowledge structure's overall degree of organization.

Empirical evidence suggests that mental models have important implications for individual performance (Day et al., 2001; Dorsey et al., 1999; Schuelke et al., 2009).

Many researchers have articulated the informational value of using mental models as an explanatory mechanism (Alba & Hasher, 1983; Cannon–Bowers & Salas, 2001). Specifically, mental models allow individuals to predict and explain events and form expectations based on the recognition of relationships. Furthermore, well developed mental models allow individuals to vicariously experience events (Johnson–Laird, 1983) and mentally manipulate model parameters to anticipate expected outcomes in novel situations. Mental models can also serve as a diagnostic aide in that mental models can help teams and individuals evaluate their knowledge and analyze effective and ineffective performance (Jagacinski & Miller, 1978; Sanderson, 1989).

Measuring knowledge is of much value to the I/O field as a whole and to training in particular. Knowledge assessment using mental models allows for the identification of content and structure useful for predicting performance (Cooke et al., 2003). In turn, the insights made available through mental model assessments provide significant resources for the design of training content.

As previously mentioned, assessments of knowledge structures are associated with limitations and challenges. For instance, Pathfinder requires participants to make pair–wise comparisons between concepts. As such, the number of concepts relates to the number of pair–wise comparisons by the function $k(k–1)/2$, where k equals the number of concepts. For example, Day et al. (2001) investigated the relationship between mental models and task performance using 14 terms which required participants to generate 91 pair–wise comparisons. Eliciting pair–wise comparisons presents two challenges to researchers. First, the administration time required to complete the assessment is a function of the number of concepts. Day et al. allowed 20 minutes for participants to complete the Pathfinder assessment with 14 terms. Thus, an extrapolation suggests that if an additional five terms were used (i.e., 19 terms), the administration time would double to 40 minutes.

Second, due to administrative constraints, researchers tend to limit the number of terms used in mental model assessments. Goldsmith, Johnson, and Acton (1991) noted that the quality of a mental model depends greatly on how many concepts are chosen to represent the domain. Based on their comparisons of structures using 30 concepts and randomly selected subsets of 5, 10, 15, 20, and 25 concepts each, they concluded that mental model predictive validity is a linear function of the number of concepts (i.e., higher predictive validities were found for subsets with more concepts). See Figure 1 for a graph of their findings.

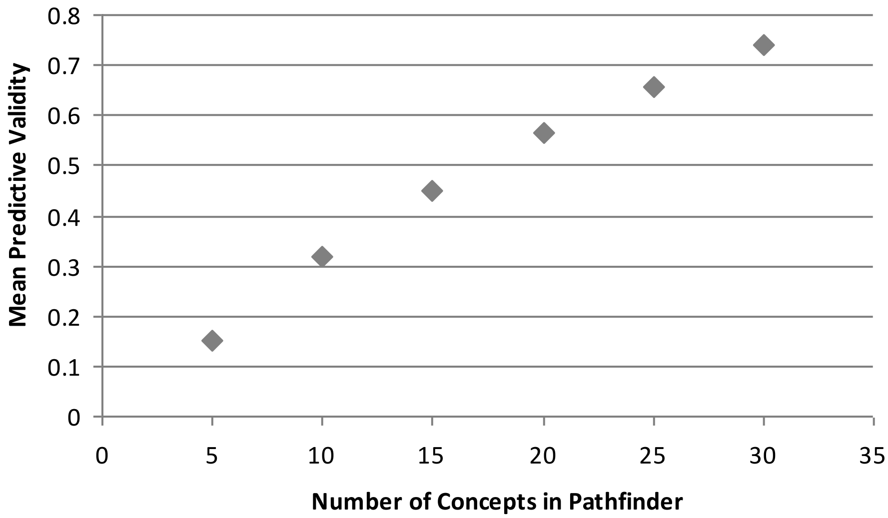


Figure 1. Predictive validity based on number of Pathfinder concepts. The figure shows the linear function between the number of concepts in Pathfinder assessments and the average predictive validity of the resulting mental model networks (Goldsmith et al., 1991).

Goldsmith et al. (1991) investigated the possibility that certain relationships between concepts result in higher validity than others by testing subsets of concepts (e.g., one subset of 15 concepts was found to have a mean predictive validity of .78 as compared to .74 for all 30 concepts). The subsets examined were found to predict performance at or below the average of all the concepts. Thus, the authors concluded that mental model predictive validity depends on the number of concepts and stabilizes across samples—in this case, students—when an adequate number of concepts are included. This is informative to the present study because it provides some evidence that a greater number of concepts likely leads to an increase in predictive validity beyond any specific subset of concepts. Although the authors did not explicitly define the exact number of concepts for optimal validity, the data provide compelling support that more concepts will result in greater predictive validity of mental models. However, greater domain representation in the form of more concepts can also be quite a hindrance to the process of eliciting mental models.

Goldsmith and Kraiger (1996) reported that the typical number of concepts used in their research was around 20 to 30—representing only a subset of concepts deemed important by subject matter experts (SMEs). Additionally, in a brief review of five studies (Day et al., 2001; Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000; Lim & Klein, 2006; Marks, Sabella, Burke, & Zaccaro, 2002; Rentsch & Klimoski, 2001), the mean number of terms used in Pathfinder analyses was 12.20 (*SD* = 3.03, min = 8, max = 15). Although concepts are entirely domain-dependent, adequate representation is clearly impacted by this significant practical constraint.

The limitation surrounding domain representation is particularly problematic for complex tasks—a domain that is often of interest to mental model researchers. For example, driving may consist of as many as 92 tasks (McKnight & Adams, 1971), which would result in as many as 4,186 pair–wise comparisons (assuming all tasks were used). Thus, researchers must make a choice between a representative list of terms or limiting the number of terms and decreasing representativeness. From a job analysis perspective, one may use higher–order task statements (or major work behaviors) to capture the entire job domain. However, the number of tasks and concepts may exceed the administrative limitations when sufficient detail is needed, as is the case with mental model assessment.

Clariana and Wallace (2009) compared three types of mental model assessments based on the predictive validity and efficiency in administration of each. They found that on average, the pair-wise elicitation method required the most time to complete (447.4*s*) compared to list-wise (193.3*s*) and clustering (115.5*s*) approaches. In a follow-up study, Singh (2007) specifically evaluated the extent to which participants expressed fatigue, enjoyment, and decreased focus as a function of the number of concepts in the pair-wise and clustering methods. Two conditions for each method were designed to assess these effects. Specifically, participants were assigned to complete one of the Pathfinder assessments, which included either a high (k = 21) or low (k = 8) number of concepts. Following the Pathfinder assessment, participants completed reaction measures to assess levels of fatigue, attention, and enjoyment experienced during the task.

Results showed strong relationships between mental model coherence and fatigue ($r = -.65$, $p < .01$) and between coherence and enjoyment ($r = .58$, $p < .01$), illustrating that the quality of a mental model is affected by respondent reactions to the assessments. She also found that participants in the conditions with fewer concepts reported significantly less fatigue, F (2, 36) = 25.37, $p < .01$, $\eta^2 = .44$. Additionally, participants who completed the pair-wise measure with fewer concepts reported having more attention, t (16) = 1.91, $p < .05$, d = 0.90. Taken together, these results highlight the impact of an onerous mental model assessment method—namely that participants do not enjoy making large numbers of pair-wise comparisons, and their resulting reactions to such measures may impact the usefulness of the mental models derived.

Importance Ratings

Given the administrative limitations and constraints associated with the use of mental model assessment methods that use pair–wise comparisons, a common methodology in structural knowledge measures (e.g., Cannon-Bowers et al., 1999; Day et al., 2001; Edwards et al., 2006; Marks et al., 2002), researchers are interested in identifying alternative measurement methods that do not engender said limitations and constraints (DeChurch & Mesmer–Magnus, 2010; Mohammed, Ferzandi, & Hamilton, 2010).

Mohammed et al. (2010) provide an informative review of knowledge structure measurement strategies. In their review, they highlight the need for alternative methods of assessment, as well as studies that simultaneously assess multiple methods of assessment. For instance, Cooke and colleagues (Cooke, Kiekel, & Helm, 2001; Cooke et al., 2003) reported that Pathfinder ratings were more strongly correlated with performance on an uninhabited air vehicle simulation compared to questionnaires that did not capture model structure. The researchers noted that the elaborate nature of knowledge content and structure translates into differing uses across knowledge measures—an important consideration in the comparison of mental model assessments.

Other efforts towards identifying less burdensome mental model assessments are represented in the investigation by Webber, Chen, Payne, Marsh and Zaccaro (2000). The authors used a ratings approach based on an established performance appraisal technique of critical incidents to capture strategic team mental models. This study provides valuable evidence that mental models generated from ratings can be used to predict performance, a finding that the present study aims to replicate.

DeChurch and Mesmer–Magnus's (2010) meta–analysis confirms the finding that knowledge generated from ratings can predict performance and further suggests that the mental model measurement strategy moderates the observed relationships between shared mental models and outcomes. Specifically, their results suggest that model structure is particularly important for predicting team processes but not performance. Mental model measurement strategies that capture model structure—pair–wise comparison and card sorting (or concept mapping)—did not meaningfully differ in terms of relationships to performance ($\rho = .31$ for both strategies) compared to methods that did not capture model structure ($\rho = .32$). As such, the additional limitations and constraints associated with assessments aimed at capturing model structure may be avoided if predicting performance is the primary focus of the research effort.

A similar alternative measurement strategy is importance ratings. Importance ratings are posited to reflect an individual's understanding and perceptions of the task domain. As such, individual differences in perceptions should predict performance such that individuals with a more accurate perception of task demands should perform better than those with less accurate perceptions. Theoretically, this proposition is supported based on the well-established link between knowledge and performance (Hunter, 1986). The degree to which individuals are accurate on their knowledge of each concept's importance should allow for differentiation in performance outcomes. Furthermore, importance ratings may reflect how participants prioritize information and subtasks thus reflecting an individual difference in motivation to perform specified tasks, guide decisions, and direct attention and behavior.

Importance ratings of task statements and knowledge, skills, abilities, and other characteristics are widely used in I/O psychology and have a longstanding history of being used to analyze and inform researchers about job and task content (Brannick, Levine, & Morgeson, 2007). For example, hybrid job and task analysis methods—such as the combination job analysis method—rely on importance ratings to provide task importance values that represent the difficulty and criticality of each task. Importance ratings are also used to evaluate the necessary knowledge, skills, and abilities for job selection purposes. Thus, importance ratings provide knowledge used to guide decisions and procedures for researchers and practitioners alike. Although importance ratings are largely a perceptual measure, researchers have found empirical evidence that perceptions of relative importance can shed considerable light on meta-cognitions surrounding decision making (Goldstein, 1990; Goldstein & Mitzel, 1992).

Several studies have evaluated the extent to which importance ratings converge with traditional mental model assessment methods. One study—Schvaneveldt, Beringer, and Lamonica (2001) —found support for using importance ratings to predict differences between novice and more experienced pilots. Specifically, Schvaneveldt et al. investigated differences between importance ratings and mental models assessed using pair–wise comparisons for both groups of pilots. In evaluating the expert and novice results, significant differences were found such that of the 16 concepts, 11 were rated more important by expert pilots compared to novice pilots. In a follow–up study, 34 pilots provided Pathfinder ratings; the results suggested that expert and novice pilots had similar mental models. However, because the previous study used a relatively small sample and did not investigate importance ratings and mental models relationships with performance, an objective of the present study is to replicate these findings.

Resick, Murase, Bedwell, Sanz, Jimenez, and DeChurch (2010) directly compared Pathfinder, priority rankings, and importance ratings in a team decision-making task. The results showed that Pathfinder's predictive validity was superior to either of the other assessment methods. While this study highlights the ongoing research attempts to identify and validate alternative mental model metrics, the present study contributes to further exploration of importance ratings as a viable alternative by expanding the research question to individual-level performance on driving—a complex task.

Importance ratings assess the content of the task domain, but unlike mental models, importance ratings do not capture mental model structure. Although importance ratings do not provide relational information between terms, they do provide relational information between the terms and the overall task. Specifically, the importance rating stem in the current study instructed participants to rate the importance of each concept "as it relates to driving safely." Thus, the importance rated by participants provides insight to their knowledge of concepts relevant to the overall task of safe driving. However, the present study does not intend to confirm or deny whether importance ratings capture structural knowledge. For comparative purposes, it is speculated that importance ratings fall more closely to the declarative end of a continuum of knowledge measures while traditional pair-wise mental model assessments fall closer to the procedural end of the same continuum.

Although the comparison of importance ratings and mental models in predicting performance is not new, the present study provides an important contribution to this distinction as it applies to predicting individual knowledge and performance on a complex task. To this end, the present study assessed the comparative effectiveness of importance ratings and mental models in predicting driving outcomes.

Driving Performance

Vehicular crashes are the most common cause of death on the job representing 39% of all fatal work injuries (U.S. Department of Labor, Bureau of Labor Statistics, 2010). As such, driving is of interest to I/O psychologists (e.g., Elliott, Armitage, & Baughan, 2003; Legree, Heffner, Psotka, Martin, & Medsker, 2003; Newman, Griffin, & Manson, 2008). Researchers in this domain distinguish between information processing errors and violations of safe driving practices as anomalous behaviors (Arthur & Day, 2009; Arthur, Barrett, & Alexander, 1991; Parker, Reason, Manstead, & Stadling, 1995; Reason, 1990) and posit that they have differential effects on critical driving outcomes (e.g., moving violations, vehicle crashes). Specifically, errors result from failures in information processing, whereas violations result from motivation, values, and attitudes. As such, Arthur and Day (2009) posit that different clusters of individual differences will predict different aspects of driving behavior.

State regulations typically require driver license applicants to pass a knowledge test in order to receive a driver's license. Furthermore, efforts to prevent vehicle crashes and unsafe driving practices typically focus on driver education. These policies reflect a belief that driving knowledge is associated with driving performance. However, although driving knowledge has received considerable research attention (e.g., Arthur & Doverspike, 2001; Legree et al., 2003; Struckman–Johnson, Lund, Williams, & Osborne, 1989), the empirical support for the knowledge–performance relationship in the context of driving is equivocal (Arthur & Doverspike, 2001; Struckman–Johnson et al., 1989). One potential explanation for the weak observed correlation between written driving knowledge test scores and crash involvement is that crash involvement is influenced by attitudinal variables as much as it is by ability variables (Arthur & Day, 2009). This has led researchers to investigate a myriad of other individual differences, including demographic, exposure, information–processing, and personality variables (Arthur et al., 1991; Elander, West, & French, 1993; Hansen, 1989). However, another plausible explanation for the lack of relationship between driving knowledge and crash involvement is that declarative knowledge focuses on the amount of knowledge, whereas knowledge organization may be more predictive of crash involvement. This position is supported by theory put forth by Ackerman (1988) in which he describes a learning acquisition model to explain the development of skill acquisition over time. Specifically, this empirically supported model informs that declarative knowledge is predictive of performance primarily in the early stages of skill development. In the domain of driving performance, declarative knowledge may be useful for predicting performance to the extent that knowledge is needed to master the required laws and rules of the road. Beyond this threshold of the learning curve, it is likely that declarative knowledge no longer provides utility in predicting driving performance outcomes. Thus, the primary research question of the present study is to evaluate the comparative effectiveness of importance ratings and mental models in predicting driving performance. Specifically, the present study sought to investigate whether importance ratings predict driving outcomes as well as a mental model measurement that utilizes relatedness ratings.

METHOD

Participants

Participants consisted of 118 undergraduate students from a large southwestern university drawn from the undergraduate psychology research subject pool. The mean age of the participants was 18.65 years (*SD* = 0.77) and 59 (51.3%) of them were female. On average participants had been driving for 2.99 years (*SD* = 1.14, min = 1.00, max = 6.00).

Materials and Procedure

General Mental Ability (GMA). Participants first completed the Raven's Advanced Progressive Matrices (short form), which consists of two practice items and 12 test items. This measure of GMA has a reported test–retest reliability of .76 and has an administration time of 15 minutes (Arthur, Tubre, Paul, & Sanchez–Ku, 1999).

Driving Behavior Questionnaire. The Driving Behavior Questionnaire (Arthur & Doverspike, 1992) is a self–report measure of driving behavior (see Appendix A). Participants reported the number of at–fault crashes and moving violations they received in the past five years (i.e., since 2005). Participants also provided information regarding their driving experience including the number of years they have been driving.

Driving Knowledge. The Driving Knowledge Test was an 18–item, multiple choice exam. It was the road rules section of a retired operational Texas state driving exam (Texas Department of Public Safety, 1984). Each question consisted of a stem followed by four alternatives, only one of which was the correct answer. All items were based on the state driving manual. The total score was the number of items answered correctly.

Pathfinder. Pathfinder (Schvaneveldt, 1990), a structural-assessment-technique-based program, was used for the elicitation, analysis, and comparison of driving mental models. The 12 driving-related concepts included in the measure were developed through a content analysis of the Texas state driving manual. Next, these concepts were reviewed and revised by one I/O psychology faculty member and two senior I/O Ph.D. candidates.

Participants were asked to make judgments about the relatedness of all possible pairs of concepts. In the administration of Pathfinder, trainees first read the instructions and then made similarity (i.e., relatedness) ratings on all possible pairs of the 12 driving concepts resulting in a total of 66 ratings. For each pair of concepts, participants were asked to indicate the extent to which they were related by using a graphic of 4 concentric circles (i.e., a bull's–eye; see Figure 2). Each circle represented a different level of relatedness consisting of synonym, extremely related, largely related, and moderately related. Concepts could also be placed outside the concentric circles in which case the concepts were considered less related or unrelated (see Figure 2).

Mental model networks were derived with Pathfinder algorithm parameters set to $r = \infty$ and q = number of concepts less one. To test for the accuracy of participants' mental models, the degree of similarity between the participants' mental models and expert referent mental model was assessed. The expert referent model is discussed in detail later. Specifically, accuracy was assessed by computing closeness (C; Goldsmith

& Davenport, 1990). *C* is roughly equal to the ratio of the number of links shared between two models divided by the total number of links. The values of *C* can range from 0 to 1, with 1 representing perfect similarity. Coherence was also assessed, which reflects the extent to which there is a meaningful pattern in how concepts are arranged (Goldsmith & Kraiger, 1996). Specifically, coherence scores are correlations between direct relatedness ratings and derived indirect ratings (Interlink, 1992; Stout, Salas, & Kraiger, 1997).

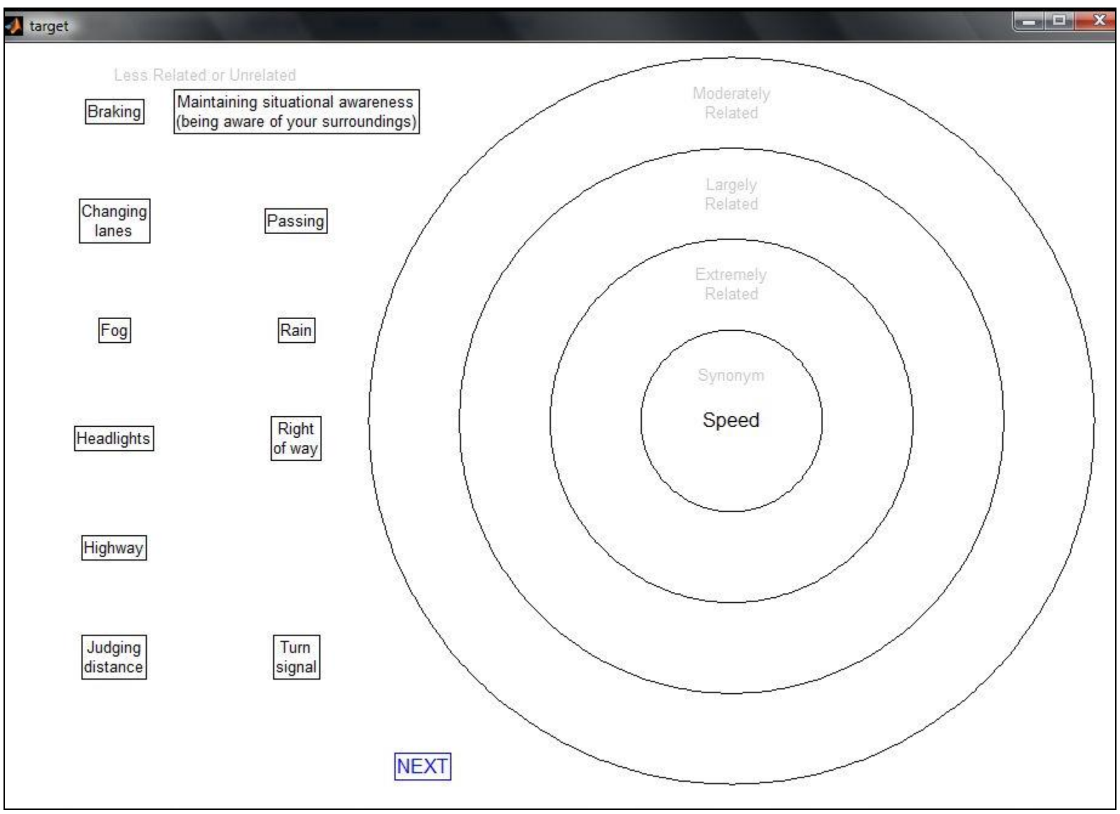


Figure 2. Pathfinder screen. This figure illustrates the mental model assessment measure used to capture relationships between concepts related to safe driving. Participants clicked and dragged concepts related to the central focal concept to the appropriate level of relatedness. Unrelated concepts were left along the left side, outside of the circles.

Importance Ratings. Following the Pathfinder ratings, participants immediately completed the importance rating form, which consisted of the same 12 driving–related concepts that were included in the Pathfinder mental model measure described above. (See Appendix C for the complete importance rating measure.) The Pathfinder and importance rating measures were not counter-balanced—all participants first completed the Pathfinder assessment and then provided ratings on the importance of each concept. The limitations and threats associated with this procedure are note in the Discussion and Conclusions section.

Participants rated each concept on a 5–point scale, with 5 representing extremely important concepts and 1 representing unimportant ones. Accuracy was assessed based on the degree of similarity between participant importance ratings and expert importance ratings (described in detail below) by computing the absolute difference between participant and expert ratings. For ease of interpretation, the importance rating accuracy was reverse coded. Specifically, deviation scores for each concept were represented by the absolute value of the difference between the referent true score and each participant's rating. This value was then subtracted from 4 so that the final accuracy index could be interpreted as higher scores reflecting greater accuracy on a scale from 0 to 4. For example, a participant rating of 4 as compared to a referent score of 5 (i.e., a total deviation of 1) would produce an accuracy index of 3 for that concept. The total accuracy index is a sum of the reverse-coded deviation scores across all concepts for each participant.

Referent Scores. To assess the accuracy of both importance ratings and mental models, five male police officers were recruited to serve as SMEs. All SMEs were active police officers with considerable experience ranging from 4 to 25 years (*M* = 18.40 years, *SD* = 8.35), and extensive training. Specifically, all SMEs were currently serving as crash reconstruction officers with the local city police department. As such, they received extensive training in defensive driving, crash investigation, crash reconstruction, and traffic enforcement. SMEs provided importance ratings and mental model ratings using the same procedures described previously.

Table 1 presents the individually collected importance ratings and mental model indices of coherence and number of model links for each SME. SME 1 was discovered to have an unacceptable coherence score demonstrating a lack of discernible structure within his mental model. As a result, averaged importance ratings and mental model scores were computed for all SME subgroups excluding SME 1. Table 2 presents the interrater agreement analyses and combined mental model indices for these SME subgroups.

A comparison of the resultant importance ratings and mental models suggests only two SMEs provided ratings that displayed acceptable psychometric properties across both measures (SME23). Subsequently, the two mental models were averaged within the Pathfinder program to yield one referent structure, which had a *C* of .52, and a coherence of .34. Importance ratings from these two experts were averaged, and the two sets of ratings displayed high levels of inter-rater reliability (.90).

Table 1

SME Importance Ratings and Mental Model Indices

Concept	SME1	SME2	SME3	SME4	SME5
Braking	5	5	5	5	3
Changing lanes	5	4	4	5	2
Fog	5	4	5	5	3
Headlights	3	3	3	4	3
Highway	4	2	3	5	3
Judging distance	5	5	5	5	4
Situational awareness	5	5	5	5	5
Passing	4	4	4	4	3
Rain	4	4	4	5	3
Right of way	4	5	4	4	3
Speed	5	4	4	5	4
Turn signal	4	4	4	5	3
MM coherence	-.02	0.26	0.28	0.53	0.27
Number of links	42	34	26	36	23

Note. SME = subject matter expert. MM = mental model.

Table 2

Importance Rating Interrater Agreement and Mental Model Indices for SME Subgroups

SME	*IR α*	*MM Coherence*	*Number of links*
SME23	0.90	0.34	19
SME24	0.57	0.46	24
SME25	0.54	0.40	19
SME34	0.59	0.51	19
SME35	0.59	0.33	15
SME45	0.63	0.41	15
SME234	0.70	0.16	26
SME235	0.78	0.37	25
SME245	0.55	0.01	26
SME345	0.61	0.01	25
SME2345	0.71	0.34	19

Note. SME = subject matter expert. IR = importance ratings. MM = mental model. Alphas are standardized. SME combinations calculated for only those with coherent mental models (SME 1 did not meet the coherence threshold of .20).

RESULTS

Frequencies for both driving performance criteria are shown in Table 3. A larger percentage of participants reported moving violations (28%) as compared to at-fault crashes (22%). Table 4 presents the descriptive statistics and correlations among the study variables. Regarding the driving performance outcomes, moving violations and at-fault crashes were significantly positively correlated ($r = .33$, $p < .01$).

Table 3
Frequencies of Reported Driving Performance Outcomes

	At-Fault Crashes		Moving Violations	
	Frequency	Percent	Frequency	Percent
None	92	0.78	85	0.72
1	16	0.14	18	0.15
More than 1	10	0.08	15	0.13

Importance ratings were positively correlated with both the number of years driving ($r = .21$, $p < .05$) and cognitive ability ($r = .18$, $p < .05$). Driving knowledge was correlated with mental models ($r = .20$, $p < .05$), such that higher scores on the driving test were associated with greater mental model accuracy. Correlations between the predictors of interest and the criteria were in the directions proposed such that greater mental model and importance ratings accuracy are both associated with fewer adverse driving outcomes; however, these were not statistically significant.

To determine the incremental predictive validity of the importance ratings and mental model accuracy measures, demographics (i.e., age and sex), cognitive ability, declarative knowledge, and number of years driving (these will be considered commonly used predictors for simplicity in reporting), were entered in the first block of the hierarchical regression. Then importance ratings or mental model indices were entered in the second block, followed by the remaining predictor (either mental models or importance ratings) in the third block.

Table 5 presents the results from hierarchical regression analysis of the accuracy indices on driving performance. The measure of variance accounted for, R^2 and ΔR^2, in predicting driving outcomes from commonly used predictors, individual mental models, and importance ratings indices are shown in the order they were entered in the model. Of note is that none of the models were significant in predicting at-fault crashes. However, all models were significant in predicting the number of moving violations.

The first block—commonly used predictors—accounted for 8% of the variance ($p > .05$) in predicting at–fault crashes. When entered following these predictors, mental models accounted for only a small amount of incremental variance ($\Delta R^2 = .01$, $p > .05$). Importance ratings were able to explain a significant amount of incremental variance when entered after the commonly used predictors ($\Delta R^2 = .02$, $p < .05$).

Next, the same hierarchical regression analysis was performed with number of moving violations. The commonly used predictors entered in the first block were able to explain 10% of the variance in number of moving violations; the overall model was significant at $p < .05$. In the following step, importance ratings were unable to explain any unique variance in number of moving violations ($\Delta R^2 = .03$, $p > .05$). However, mental models explained significant incremental variance over the commonly used predictors ($\Delta R^2 = .05$, $p < .01$).

To assess whether mental model accuracy provides incremental predictive validity beyond importance rating accuracy, a third model was tested in which mental model accuracy was entered in the model after commonly used predictors and importance rating accuracy. This overall model was not predictive for at-fault crashes, and importance rating accuracy and mental model accuracy each provided minimal predictive validity beyond commonly used predictors. However, the amount of additional variance accounted for (ΔR^2) was significant for importance rating accuracy but not for mental model accuracy.

In the prediction of moving violations, mental model accuracy continued to out-predict importance rating accuracy even when entered in the same model following importance rating accuracy. Specifically, mental model accuracy accounted for an additional 4% of the variance in moving violations beyond the proportion of variance accounted for by commonly used predictors and importance rating accuracy.

Table 4

Descriptive Statistics and Zero-order Correlations Among All Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Age	18.65	0.78	–							
2. Sex	0.48	0.50	.21*	–						
3. Years driving	2.99	1.13	.45**	.23*	–					
4. Cognitive ability	8.10	2.32	.13	.13	.09	–				
5. Driving knowledge	12.56	2.00	–.11	–.03	.11	.15	–			
6. Mental model accuracy	0.12	0.08	.09	–.06	.03	.17	.20*	–		
7. Importance rating accuracy	36.57	5.57	.02	–.05	.21*	.18*	.09	.13	–	
8. At-fault crashes	0.37	0.68	–.04	–.16	.12	.07	.00	–.11	–.11	–
9. Moving violations	0.67	1.71	.02	.04	.30**	.05	.00	–.15	–.03	.33**

Note. $N = 118$. Sex: 0 = female, 1 = male. Higher mental model scores and higher importance rating scores indicate greater accuracy. Crash and moving violation information based on incidents from 2005 to 2009. *$p < .05$. ** $p < .01$. All tests are two-tailed.

Table 5

Hierarchical Regression Analyses of Accuracy Indices on Driving Performance

Model	Predictor	At-fault Crashes R^2	At-fault Crashes ΔR^2	Moving Violations R^2	Moving Violations ΔR^2
1	Commonly used predictors	.08		.10*	
	Importance rating accuracy	.10	.02*	.13*	.03
2	Commonly used predictors	.08		.10*	
	Mental model accuracy	.09	.01	.15**	.05**
3	Commonly used predictors	.08		.10*	
	Importance rating accuracy	.10	.02*	.13*	.03
	Mental model accuracy	.11	.01	.17**	.04*

Note. $N = 118$. Each line indicates a new block in the hierarchical regression. Commonly used predictors are age, sex, cognitive ability, number of years driving, and driving knowledge test. *$p < .05$. ** $p < .01$.

DISCUSSION AND CONCLUSIONS

Importance ratings and mental models were comparatively evaluated in terms of their ability to predict driving outcomes—crashes and moving violations. The objective of the present study was to investigate the extent to which importance ratings displayed similar relationships with driving outcomes compared to mental models.

On the basis of the observed results, it would seem that importance ratings and mental models measured distinct constructs. The two measures are conceptualized as representing two different kinds of knowledge, which were demonstrated to perform differently in the prediction of driving crashes and moving violations. It was found that importance ratings, but not mental models, provided significant incremental validity in predicting at–fault crashes; the increased predictive validity was small for both measures. Mental models and importance ratings displayed incremental validity over commonly used predictors. The results demonstrate that importance ratings may be a viable alternative to traditional mental model assessments in predicting crash involvement.

Differences were found between the variance explained by importance ratings and mental models when predicting number of moving violations. Mental models explained more variance in the number of moving violations than did importance ratings. Moving violations are viewed as more motivational and attitudinal in nature (Arthur & Day, 2009), which may explain this finding. It is possible that importance ratings do not accurately capture attitudes and values towards driving in addition to driving performance.

Implications, Limitations, and Future Research

Although the results found in the present study are mixed, they contribute to the literature on alternative mental model assessments in providing some evidence of predictive validity for importance ratings on a complex task. Additionally, the present study is consistent with meta-analytic findings that suggest structure is not a necessary component for knowledge assessments that are meant to predict performance (DeChurch & Mesmer-Magnus, 2010)

It is important to note that the present study did not seek to validate importance ratings as an alternative type of mental model but rather as a knowledge measure with potentially equal predictive validity for driving performance. In this view, the findings help shed light on the extent to which importance ratings are a useful measure in this domain—predicting adverse driving events.

There are also implications for the measurement of knowledge in other domains. Specifically, mental model measurement is associated with administrative constraints and limitations (Clariana & Wallace, 2009; Singh, 2007). Mental model researchers may be constrained in the number of concepts they can use (Goldsmith et al., 1991), as the number affects administration times and likely test–taker motivation as well (Singh, 2007). As demonstrated in this study, importance ratings may offer a less onerous measure compared to mental models, and are not associated with similar administrative limitations and constraints.

Although the results are favorable towards continued research on the validity of importance ratings as alternative to mental models, there are limitations and recommendations to improve the methodology and guide future studies. First, some difficulty was encountered when computing the referent structures and ratings from the SMEs. A suggested solution is to involve different SMEs in developing the concepts recognizing that a second and separate group of SMEs would then be needed to actually provide the referent scores. Second, although detailed instructions on the measurements were provided, it was assumed participants and experts held similar meanings of "safe driving." The context-dependent definition is of particular importance in measuring knowledge structures as it provides raters with the target situation they should think of when rating the concepts. Mental models within specific contexts are referred to as situation models. It is possible that different drivers envision varying situation models when asked about safe driving. Regarding this effect, future importance ratings measurements should also evaluate perceptions of overall task importance, which may add an evaluation of the participant’s motivations for performing the task in addition to cognitions of performing the task.

An important next step in this line of research is to gather data on the actual administration times of Pathfinder and alternative measures. In the present study's protocol, participants were allotted roughly 10 minutes to complete the Pathfinder assessment and 2 minutes to complete the importance ratings; however, no restrictions on time were imposed (i.e., participants could have taken longer), and actual completion times were not measured. Additionally, the effect of participant reactions to the measures could be collected in future studies to investigate whether meaningful differences are found between the measures similar to those reported by Singh (2007).

Additionally, importance ratings and the pair-wise assessment method should be compared based on differing numbers of concepts. As Goldsmith et al. (1991) demonstrated, increasing the number of concepts should only serve to improve predictive validity. However, it is unknown at this time whether an importance rating measure with a greater number of concepts would result in higher predictive validity than a pair-wise mental model measure with fewer concepts. Based on the results of this study, it seems quite possible.

The potential effect of not counter-balancing the importance rating and mental model measures is a significant limitation of the present study. This may have had an impact on participants' ratings of task concept importance as these ratings always followed the completion of Pathfinder. Because Pathfinder is associated with a greater number of ratings and potentially increased negative reactions, the accuracy of participant importance ratings may have been affected due to decreased focus or increased fatigue.

Another important limitation in the present study is the use of a sample of undergraduate drivers. This sample may have had reduced variability in driving performance because the participants have been driving for an average of 2.99 years. Additionally, the low frequency of at-fault crashes in this sample makes it more difficult to obtain statistical significance for known predictors of such outcomes (Arthur et al., 1991; Elander, West, & French, 1993; Hansen, 1989). Stronger conclusions may be found in a more diverse sample. Future research should compare importance ratings and mental models in other complex task domains to investigate the generalizability of these findings.

Novel approaches to measuring knowledge structures provide valuable insights to the relationship between mental models and performance. Importance ratings as measured in the present study are not only more convenient to measure for researchers and complete for participants but also work as well as mental models in predicting at-fault crash involvement. The present study represents one attempt to assess and validate an alternative approach to assessing knowledge organization in a more convenient fashion.

REFERENCES

Ackerman, P. L. (1988). Determinants of individual differences during skill acquisition: Cognitive abilities and information processing. *Journal of Experimental Psychology, 117,* 288-318.

Alba, J. W., & Hasher, L. (1983). Is memory schematic? *Psychological Bulletin, 93,* 203–231.

Arthur, W. Jr., Barrett, G. V., & Alexander, R. A. (1991). Prediction of vehicular accident involvement: A meta-analysis. *Human Performance, 4,* 89–105.

Arthur, W. Jr., & Day, E. A. (2009). Information processing, personality, and demographic variables as predictors of crashes and moving violations. In G. P. Bartley (Ed.), *Traffic accidents: Causes and outcomes* (pp. 97–121). New York: Novinka/Nova Science Publishers.

Arthur, W. Jr., & Doverspike, D. (2001). Predicting motor vehicle crash involvement from a personality measure and a driving knowledge test. *Journal of Prevention and Intervention in the Community, 22,* 35–42.

Arthur, W. Jr., & Doverspike, D. (1992). Locus of control and auditory selective attention as predictors of driving accident involvement: A comparative longitudinal investigation. *Journal of Safety Research, 23*, 73–80.

Arthur, W. Jr., Tubre, T. C., Paul, D. S., & Sanchez–Ku, M. L. (1999). College-sample psychometrics and normative data on a short form of the Raven Advanced Progressive Matrices Test. *Journal of Psychoeducational Assessment, 17,* 354–361.

Brannick, M. T., Levine, E. L., & Morgeson, F. P. (2007). *Job and work analysis: methods, research, and applications for human resource management.* Sage Publications: Los Angeles, CA.

Cannon–Bowers, J. A., & Salas, E. (2001). Reflections on shared cognition. *Journal of Organizational Behavior, 22,* 195–202.

Clariana, R. B., & Wallace, P. (2009). A comparison of pair-wise, list-wise, and clustering approaches for eliciting structural knowledge. *International Journal of Instructional Media, 36,* 287–302.

Cooke, N. J., Kiekel, P. A., & Helm, E. E. (2001). Measuring team knowledge during skill acquisition of a complex task. *International Journal of Cognitive Ergonomics, 5,* 297–315.

Cooke, N. J., Kiekel, P. A., Salas, E., Stout, R., Bowers, C., & Cannon-Bowers, J. (2003). Measuring team knowledge: A window to the cognitive underpinnings of team performance. *Group Dynamics: Theory, Research, and Practice, 7*, 179–199.

Cooke, N. J., Salas, E., Cannon–Bowers, J. A., & Stout, R. J. (2000). Measuring team knowledge. *Human Factors, 42,* 151–173.

Day, E. A., Arthur, W. Jr., & Gettman, D. (2001). Knowledge structure and the acquisition of a complex skill. *Journal of Applied Psychology, 86,* 1022–1033.

DeChurch, L. A., & Mesmer–Magnus, J. R. (2010). Measuring shared team mental models: A meta-analysis. *Group Dynamics: Theory, Research, and Practice, 14,* 1–14.

Dorsey, D. W., Campbell, G. E., Foster, L. L., & Miles, D. E. (1999). Assessing knowledge structures: Relations with experience and posttraining performance. *Human Performance, 12,* 31–57.

Edwards, B. D., & Day, E. A., & Arthur, W. Jr., & Bell, S. T. (2006). Relationships among team ability composition, team mental models, and team performance. *Journal of Applied Psychology, 91,* 727–736.

Elander, J., West, R., & French, D. (1993). Behavioral correlates of individual differences in road-traffic crash risk: An examination of methods and findings. *Psychological Bulletin, 113,* 279–294.

Elliott, M. A., Armitage, C. J., & Baughan, C. J. (2003). Drivers' compliance with speed limits: An application of the theory of planned behavior. *Journal of Applied Psychology, 88,* 964–972.

Goldsmith, T. E., & Davenport, D. M. (1990). Assessing structural similarity of graphs. In R. W. Schvaneveldt (Ed.), *Pathfinder associative networks: Studies in knowledge organization* (pp. 75–87). Westport, CT: Ablex Publishing.

Goldsmith, T. E., & Kraiger, K. (1996). Applications of structural knowledge assessment to training evaluation. In J. K. Ford, S. Kozlowski, K. Kraiger, E. Salas, & M. Teachout (Eds.), *Improving training effectiveness in work organizations* (pp. 73–96). Hillsdale, NJ: Erlbaum.

Goldsmith, T. E., Johnson, P. J., & Acton, W. H. (1991). Assessing structural knowledge. *Journal of Educational Psychology, 83,* 88–96.

Goldstein, W. M. (1990). Judgments of relative importance in decision making: Global vs local interpretations of subjective weight. *Organizational Behavior and Human Decision Processes, 47,* 313–336.

Goldstein, W. M., & Mitzel, H. C. (1992). The relative importance of relative importance: Inferring other people's preferences from relative importance ratings and previous decisions. *Organizational Behavior and Human Decision Processes, 51,* 382–415.

Hansen, C. P. (1989). A causel model of the relationship among accidents, biodata, personality, and cognitive factors. *Journal of Applied Psychology, 74,* 81–90.

Hunter, J. E. (1986). Cognitive ability, cognitive aptitude, job knowledge, and job performance. *Journal of Vocational Behavior, 29,* 340–362.

Interlink. (1992). PCKNOT [Computer software documentation]. Las Cruces, NM: Author.

Jagacinski, R. J., & Miller, R. A. (1978). Describing the human operator's internal model of dynamic system. *Human Factors, 20,* 425–433.

Johnson–Laird, P. N. (1983). A computational analysis of consciousness. *Cognition and Brain Theory, 6,* 499–508.

Kraiger, K., Ford, J. K., & Salas, E. (1993). Application of cognitive, skill–based, and affective theories of learning outcomes to new methods of training evaluation. *Journal of Applied Psychology, 78,* 311–328.

Legree, P. J., Heffner, T. S., Psotka, J., Martin, D. E., & Medsker, G. J. (2003). Traffic crash involvement: Experiential driving knowledge and stressful contextual antecedents. *Journal of Applied Psychology, 88,* 15–26.

Lim, B., & Klein, K. J. (2006). Team mental models and team performance: A field study of the effects of team mental model similarity and accuracy. *Journal of Organizational Behavior, 27,* 403–418.

Marks, M. A., Sabella, M. J., Burke, C. S., & Zaccaro, S. J. (2002). The impact of cross–training on team effectiveness. *Journal of Applied Psychology, 87,* 3–13.

Mathieu, J. E., Heffner, T. S., Goodwin, G. F., Salas, E., & Cannon–Bowers, J. A. (2000). The influence of shared mental models on team process and performance. *Journal of Applied Psychology, 85,* 273–283.

McKnight, A. J., & Adams, B. B. (1970). *Driver education task analysis*. Alexandria, VA: Human Resources Research Organization.

Mohammed, S., & Dumville, B. C. (2001). Team mental models in a team knowledge framework: Expanding theory and measurement across disciplinary boundaries. *Journal of Organizational Behavior, 22,* 89–106.

Mohammed, S., Ferzandi, L., & Hamilton, K. (2010). Metaphor no more: A 15–year review of the team mental model construct. *Journal of Management, 36,* 876–910.

Mohammed, S., Klimoski, R., & Rentsch, J. R. (2000). The measurement of team mental models: We have no shared schema. *Organizational Research Methods, 3,* 123–165.

Parker, D., Reason, J. T., Manstead, A. S. R., & Stradling, S. G. (1995). Driving errors, driving violations and accident involvement. *Ergonomics, 38,* 1036–1048.

Reason, J. T. (1990). *Human error.* New York: Cambridge University Press.

Rentsch, J. R., & Klimoski, R. J. (2001). Why do "great minds" think alike?: Antecedents of team member schema agreement. *Journal of Organizational Behavior, 22,* 107–120.

Resick, C. J., Murase, T., Bedwell, W. L., Sanz, E., Jiménez, M., & DeChurch, L. A. (2010). Mental model metrics and team adaptability: A mutli-facet multi-method examination. *Group Dynamics: Theory, Research, and Practice, 14*, 332–349.

Rips, L. J., Shoben, E. J., & Smith, E. E. (1973). Semantic distance and the verification of semantic relations. *Journal of Verbal Learning and Verbal Behavior, 12,* 1–20.

Rouse, W. B., & Morris, N. M. (1986). On looking into the black box: Prospects and limits in the search for mental models. *Psychological Bulletin, 100,* 349–363.

Sanderson, P. M. (1989). Verbalizable knowledge and skilled task performance: Association, dissociation, and mental models. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15,* 729–747.

Schuelke, M. J., Day, E. A., McEntire, L. E., Boatman, P. R., Boatman, J. E., Kowollik, V., et al. (2009). Relating indices of knowledge structure coherence and accuracy to skill–based performance: Is there utility in using a combination of indices? *Journal of Applied Psychology, 94,* 1076–1085.

Schvaneveldt, R. W. (1990). *Pathfinder associative networks: Studies in knowledge organization*. Norwood, NJ: Ablex.

Schvaneveldt, R. W., Beringer, D. B., & Lamonica, J. A. (2001). Priority and organization of information accessed by pilots in various phases of flight. *International Journal of Aviation Psychology, 11,* 253–280.

Singh, M. (2007). *Comparing pair-wise and clustering techniques for eliciting structural knowledge.* Unpublished manuscript. The University of Oklahoma, Norman, OK.

Stout, R. J., Salas, E., & Kraiger, K. (1997). Role of trainee structures in aviation environments. *International Journal of Aviation Psychology, 7,* 235–250.

Struckman–Johnson, D. L., Lund, A. K., Williams, A. F., & Osborne, D. W. (1989). Comparative effects of driver improvement programs on crashes and violations. *Accident Analysis and Prevention, 21,* 203–215.

U.S. Department of Labor, Bureau of Labor Statistics. (2010). *2009 Census of Fatal Occupational Injuries*. Retrieved from: http://www.bls.gov/iif/oshcfoi1.htm

APPENDIX A

DRIVING BEHAVIOR QUESTIONNAIRE

Research ID: ____

1. Do you have any problems seeing (even after correction)?

   A. Yes
   B. No

2. Which of the following Driver's Licenses do you have? (*circle all that apply*)

   A. Class A (Vehicle over 26,000 pounds – can to anything above 10,000 pounds)
   B. Class B (Vehicle over 26,000 pounds – cannot tow anything above 10,000 pounds)
   C. Class C (Any passenger vehicle)
   D. Class M (motorcycles, mopeds, etc)

3. How long have you been driving (*Round off to the nearest year)* _____________ (years)

4. What types of vehicle(s) do you typically drive? (*Check all the apply*)

   A. Passenger car B. Pick–up truck
   C. Sport–utility vehicle D. Motorcycle
   E. Van F. Commercial vehicle (e.g., 18–wheeler, bus)

5. Do you own a car phone or a cellular phone?

   A. Yes
   B. No

6. On average, how many miles do you drive a week? __________ (miles)

7. On average, how many highway and/or interstate miles do you drive a week?

   ______ (miles)

8. On average, how many miles per hour under or over the speed limit do you drive?

   _______ miles per hour (For example, if you typically drive 3 miles under, put -3. If you typically drive at the speed limit, put 0. If you typically drive 6 miles over, put +6)

9. How many times have you taken a defensive driving class? ____________

10. How often do you use a safety belt when you are <u>the driver</u> of a vehicle?

A. Never
B. Rarely
C. Sometimes
D. Frequently
E. Always

11. How often do you use a safety belt when you are <u>a passenger</u> of a vehicle?

A. Never
B. Rarely
C. Sometimes
D. Frequently
E. Always

12. Which of the following best describes where you live?

A. Rural
B. Suburban
C. Urban

13. Which of the following best describes where you do most of your driving?

A. Rural
B. Suburban
C. Urban

14. How many driving/traffic accidents have you been involved in as one of the drivers in which a person was killed?

____

In how many of these were you at fault?

____

15. Excluding the accidents reported in <u>QUESTION 14</u>, how many driving/traffic accidents have you been involved in as one of the drivers in which a person suffered physical injury?

____

In how many of these were you at fault?

____

16. Excluding the accidents reported in QUESTIONS 14 and 15, how many driving/traffic accidents have you been involved in as one of the drivers in which there was damage to property?

____

In how many of these were you at fault?

____

17. Of the accidents reported in QUESTION 16, how many resulted in property damage that was greater than or equal to $750 in value?

____

In how many of these were you at fault?

18. Please list the number of accidents and moving violation tickets in each of the years listed.

Year	**At–Fault Accidents**	**Not At–Fault Accidents**	**Tickets (Moving Violations)**
2009	____________	____________	____________
2008	____________	____________	____________
2007	____________	____________	____________
2006	____________	____________	____________
2005	____________	____________	____________

APPENDIX B

IMPORTANCE RATINGS

Please rate each of the following concepts on its level of importance to driving using the scale below. Think of the terms as they relate to **driving safely**.

Name: ____ Date: _________

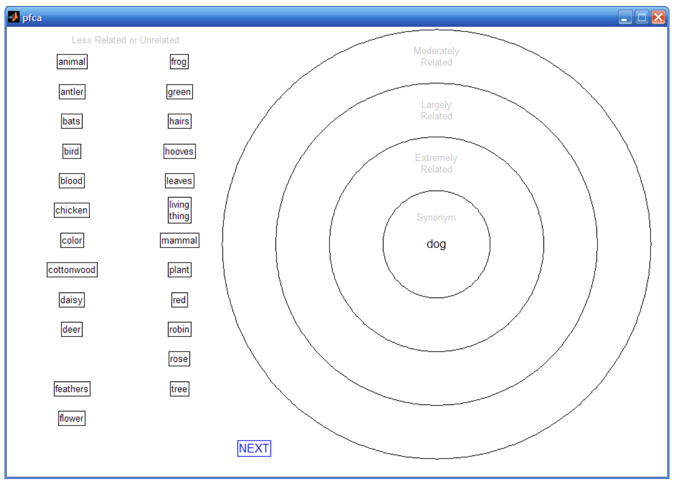
①	②	③	④	⑤
Not Important	**Somewhat Important**	**Moderately Important**	**Very Important**	**Extremely Important**

1. Braking	① ② ③ ④ ⑤
2. Changing lanes	① ② ③ ④ ⑤
3. Fog	① ② ③ ④ ⑤
4. Headlights	① ② ③ ④ ⑤
5. Highway	① ② ③ ④ ⑤
6. Judging distance	① ② ③ ④ ⑤
7. Maintaining situational awareness (being aware of your surroundings)	① ② ③ ④ ⑤
8. Passing	① ② ③ ④ ⑤
9. Rain	① ② ③ ④ ⑤
10. Right of way	① ② ③ ④ ⑤
11. Speed	① ② ③ ④ ⑤
12. Turn signal	① ② ③ ④ ⑤

APPENDIX C

PATHFINDER

In this task, you will see several concepts listed on the left hand side of the screen. Each of these concepts will be presented as a focal concept in the bull's-eye of the target on the right hand side. The example below is like what you will see. Here *"dog"* is in the bull's-eye.



Your task is to move the concepts that are *synonymous, extremely, largely, or moderately related* to the target inside the appropriate gradient of the target. Concepts that are less related or unrelated should be left in place at the left side.

To move the concepts, click and drag them to the location in which you wish to drop them. Each concept that you rate must fit into one of the five related categories (*synonymous, extremely related, largely related, moderately related, or less related/unrelated)*, there is no in–between option. Each concept will earn a score based on where the center of the concept box is located. You can change your mind about a concept by moving it again. When you finish with one target, click NEXT to proceed to the next target.

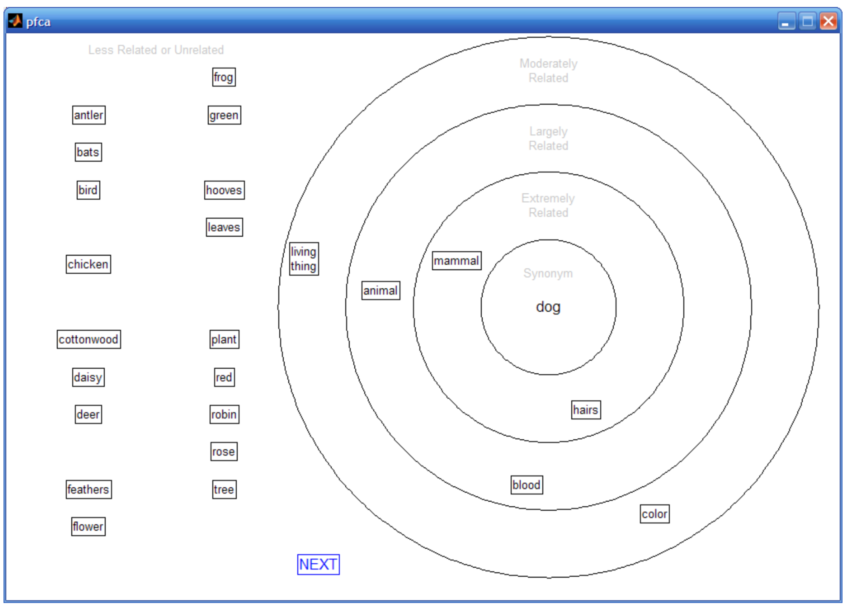
A complete list of concepts will be presented prior to beginning the task. This will give you a general idea of the scope of the concepts you will be rating.

Here are the concepts. Now, when you are doing this, do not think too much or too long. Just go with what initially comes to mind.

- Braking
- Changing lanes

- Fog
- Headlights
- Highway
- Judging distance
- Maintaining situational awareness (being aware of your surroundings)
- Passing
- Rain
- Right of way
- Speed
- Turn signal

The example below shows one person's responses for the target "*dog*". The concept "*mammal*" is in the extremely related gradient whereas the concept "*color*" is in the moderately related gradient, and so on.



Your task on the computer is to make judgments about the "relatedness" of pairs of concepts that have to do with driving. There are several ways one might think about the concepts being judged. For instance, two concepts might be related because they share common features or because they frequently occur together. For this task, think about the concepts as they relate to **driving safely.**

VITA

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